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Assessing urban population vulnerability and environmental risks across an urban area during heatwaves – Implications for health protection

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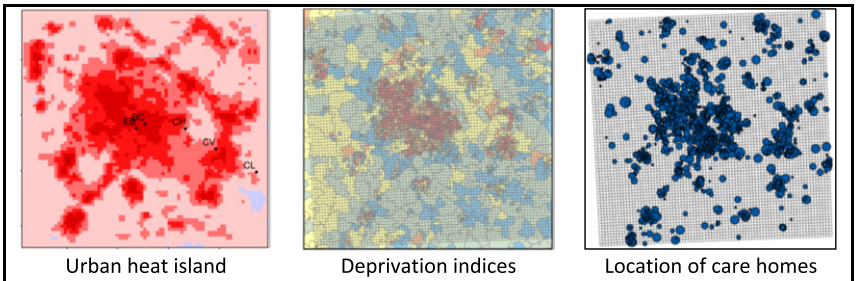
HIGHLIGHTS

- Multiple factors are associated with health effects of heat exposure.
- Cities in the West Midlands have a pronounced UHI.
- Care homes and hospitals are exposed to higher ambient temperatures than average.
- Housing types more likely to overheat are located in the warmest parts of the city.

GRAPHICAL ABSTRACT



Graphical abstract: Spatial distribution of factors that may relate to risks associated with heat-health effects across the West Midlands.

Spatial distribution of factors that may relate to risks associated with heat-health effects across the West Midlands.

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ABSTRACT

Heatwaves can lead to a range of adverse impacts including increased risk of illness and mortality; the heatwave in August 2003 has been associated with ~70,000 deaths across Europe. Due to climate change, heatwaves are likely to become more intense, more frequent and last longer in the future. A number of factors may influence risks associated with heat exposure, such as population age, housing type, and location within the Urban Heat Island, and such factors may not be evenly distributed spatially across a region. We simulated and analysed two major heatwaves in the UK, in August 2003 and July 2006, to assess spatial vulnerability to heat exposure across the West Midlands, an area containing ~5 million people, and how ambient temperature varies in relation to factors that influence heat-related health effects, through weighting of ambient temperatures according to distributions of these factors across an urban area. Additionally we present quantification of how particular centres such as hospitals are exposed to the UHI, by comparing temperatures at these locations with average temperatures across the region, and presenting these results for both day and night times. We find that UHI intensity was substantial during both heatwaves, reaching a maximum of +9.6 °C in Birmingham in July 2006. Previous work has shown some housing types, such as flats and terraced houses, are associated with increased risk of overheating, and our results show that these housing types are generally located within the warmest parts of the city. Older age groups are more susceptible to the effects of heat. Our analysis of distribution of population based on age group showed there is only small spatial variation in ambient temperature that different age groups are exposed

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to. Analysis of relative deprivation across the region indicates more deprived populations are located in the warmest parts of the city.

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1. Introduction

1.1. Heat exposure and health

Heatwaves, or extended periods of hot weather, are associated with various risks to health including heat exhaustion, heatstroke, emergency hospitalisations, and death. A severe heatwave in August 2003 has been associated with up to 70,000 excess deaths across Europe (Robine et al., 2008), with over 2000 excess deaths estimated in England (Johnson et al., 2005), and a record breaking maximum temperature of 38.5 °C reached in south east England. High temperatures were also recorded throughout much of the UK during the summer of 2006. In the West Midlands, the two heatwave events of 2003 and 2006 were comparable in terms of estimated excess mortality, being around 10% higher than baseline rates at this time of year in both cases (Health Statistics Quarterly, 2006; Johnson et al., 2005). In the future, heatwaves are projected to become more frequent, more intense, and last longer, due to climate change (Kirtman et al., 2013), which will likely lead to increases in heat-related mortality (Hajat et al., 2014; Mitchell et al., 2016; Vardoulakis et al., 2014). Some evidence suggests there is an upper limit to which humans can adapt to temperature (Arbuthnott et al., 2016; Sherwood and Huber, 2010).

In the UK, the risk of temperature-related mortality is projected to increase steeply in the UK over the 21st century under climate change and demographic change scenarios, reaching 260% by 2050, and 540% by 2080 (compared with the 2000s heat-related mortality baseline of around 2000 premature deaths), with the elderly being most at risk (Hajat et al., 2014; HPA, 2012).

Future climate projections are often produced at relatively coarse spatial resolution, due to the cost of computing power required. Factors relevant for the study of heat-exposure and human health, including population age, socioeconomic factors, and the built environment such as dwelling type and the Urban Heat Island, are at a much finer spatial scale. Our study aims to simulate ambient temperature across an urban area during a heatwave period, and subsequently quantify the variation in ambient temperature with other factors that relate to and influence heat-related health effects. This includes population-weighting of ambient temperatures, as well as calculating the ambient temperature weighted according to distributions of different housing types, population age, and deprivation score, all factors that influence heat-health relationships. Using environmental modelling techniques in this way to look at human health in relation to heat exposure during heatwaves (which will become increasingly important in the future with climate change) is a novel way of analysing spatial distribution of risks across a large urbanised region. While we have used a detailed case study here, the technique and metrics are applicable to any scenario, which we feel is useful for a wider scientific community.

1.2. The Urban Heat Island (UHI)

Populations may be particularly at risk from heat due to the Urban Heat Island (UHI) effect (Heaviside et al., 2017), whereby ambient temperatures are often observed to be higher than those in surrounding less-urbanised areas, particularly at night. The main cause of the UHI is the modification of land surfaces, for example, replacing natural surfaces (e.g. vegetation which provide natural shading and cooling via evaporation) by paving or construction of buildings. Urban construction materials (such as concrete, tarmac and asphalt) generally absorb, retain and re-radiate heat more than natural surfaces. Buildings also provide multiple surfaces to reflect and absorb sunlight, increasing urban heating, and impeding air circulation. Heat from human activities (such as air conditioning, vehicles, and industrial processes) can also add to the UHI effect. The UHI effect is often most extreme during anticyclonic summer weather conditions, which are associated with heatwaves. In England and Wales, 82% of the population reside in urban areas (ONS, 2011), leaving them vulnerable to the impacts of heat exposure due to the UHI effect. The West Midlands is a highly urbanised area of the UK, which includes the city of Birmingham with a population of 1.1 million, and has a notable UHI (Bassett et al., 2016; Heaviside et al., 2015; Tomlinson et al., 2012). A health impact assessment for the heatwave of 2003 based on high resolution meteorological modelling suggested that in the West Midlands, around half of the heat-related mortality during the heatwave could be attributed to the UHI (Heaviside et al., 2016). The UHI intensity is often defined as the difference in temperature between urban and rural areas, and can be quantified by comparing ambient air temperature observations at a location in the centre of an urban area, and at a location in surrounding rural areas (Bassett et al., 2016; Hatchett et al., 2016; Ketterer and Matzarakis, 2015; Kim and Baik, 2002; Oke, 1973, 1982), or from satellite measurements (Azevedo et al., 2016; Benz et al., 2017; Du et al., 2016). However, observation stations are limited in number, are often not sited within urban centres, and may only cover certain time periods, while satellite measurements record land surface temperature (rather than air temperature), and are often temporally limited and may have missing data if it is cloudy. The use of meteorological computer simulations makes it possible to investigate spatial variations in temperature across urban areas, and to quantify the UHI intensity, by comparing temperatures simulated both with and without urban surfaces such as buildings and roads.

1.3. Mapping spatial variation in heat-exposure and risk

Heat exposure for urban populations will vary across urbanised areas, due to spatial variations in physical infrastructure that influences the UHI. Susceptibility to health risks associated with heat exposure is also influenced by other factors, including population age, housing type, socioeconomic factors, pre-existing health conditions, and location within the UHI (Taylor et al., 2015; Wolf and McGregor, 2013). It is therefore important in terms of health protection to understand the pattern of risk across a region, which may help target resources to reduce heat risk in the most vulnerable areas, since it is possible that environmental risks and vulnerable population groups are co-located within urban areas.

A number of studies have investigated heat risk across the Greater London area. Wolf and McGregor (2013) developed a Heat Vulnerability Index (HVI) for London based on principal component analysis of socio-demographic factors relating to heat vulnerability, combined with land surface temperatures (derived from a satellite measurement), finding clustering of high vulnerability in the east and central areas of the city. Heat risk has also been mapped across London using a building physics model and monitored weather data, together with information on modelled UHI, housing type and population age, finding that building type and UHI have a significant influence on the distribution of risk across the city for summer 2006 (Taylor et al., 2015). Building fabric types and characteristics, and thus thermal properties, will depend on the age of the building, and may be an important modifier for thermal comfort and energy efficiency, in addition to behavioural aspects of building occupancy that can also modify heat exposure risk (Vardoulakis et al., 2015). An existing spatial heat risk assessment of Birmingham combined

information derived from credit reference agencies on groups such as the elderly, those with ill health, high population density, and high-rise living, finding that population sub-groups with ill health, and who reside in flats were located in the overall warmest and therefore highest heat risk areas of Birmingham (Tomlinson et al., 2011). This study used remote satellite sensing of the land surface temperature at high spatial resolution (1 km), although only a single snapshot over one night during a heatwave is used, and as such, does not fully represent the range of temperatures that population is exposed to during the heatwave period. Similar studies in large urban areas worldwide have found spatial overlap of sensitive populations and inequity in exposure to the UHI, according to age, occupation, income, and other socio-demographic indicators, and that mapping can help target efforts to reduce heat risk (e.g. via planning the location of parks, cool or green roofs, and social care efforts) (Mitchell and Chakraborty, 2015; Weber et al., 2015; Wong et al., 2016).

While mapping of risks can be a useful tool for raising public awareness of risks, it is not clear if producing maps in this way leads to policy or mitigation actions, possibly due to uncertainty in relation to policy and decision making that are difficult to address in such studies (Wolf et al., 2015). There is an increasing amount of temperature data available from satellite measurements, but this dataset only gives the temperature of the surface the satellite detects (e.g. the ground, tree tops or building roofs and walls), rather than air temperature which is more relevant for health, while the relationship between ground and air temperature is difficult to quantify. We address these issues by using simulated temperatures and quantifying heat exposure due to the UHI for populations which could be seen to be at risk.

1.4. Centres for health and social care

Care homes and hospitals are places where sensitive populations may reside. During the 2003 heatwave across Europe, of the recorded the recorded mortality among the under 75 s in the UK, more of the excess deaths were distributed in residential and nursing homes than would have been expected, and among the over 75 s, more of the excess deaths were distributed in hospitals and nursing homes (Kovats et al., 2006). In these settings there may be issues surrounding dependency on caregivers in nursing and residential homes, and the impact this may have on patients' and residents' behaviour in responding to environmental changes (e.g. disempowerment or loss of autonomy), as well as availability of assistance for daily living tasks in institutions (Belmin et al., 2007; Brown and Walker, 2008). Reports suggest care schemes have a 'culture of warmth', a perception that the elderly are vulnerable only to cold (not excessive heat), and that design for overheating is rare, with low prioritisation for future climate change and overheating (Gupta et al., 2016).

Those in prisons or custodial facilities are not able to directly access health care services, and effective ways to reduce exposure to heat may be limited. While there are few studies examining heat risk in prisons, lawsuits were successfully brought against prisons in Texas and Louisiana in the US, where inmates had died or suffered as a result of heat exposure (Human Rights Clinic, 2015; The Promise of Justice Initiative, 2013). The population in the UK is ageing, as is the prison population. Not only has the prison population in the UK increased from 56,000 to over 85,000 in the last ten years, the number of those aged 60 and over in custody are the fastest growing group, increasing by 120% from 2002 to 2013 (House of Commons, 2013; Offender management statistics quarterly, 2016). Other factors such as drug use, as well as prevalence of mental health conditions among those in custody may also contribute to health risk from exposure to heat.

1.5. Social and demographic factors

As well as the elderly, babies and young children are also vulnerable to effects associated with heat exposure (PHE, 2015). Studies have shown that warmer classrooms (25 °C compared to 20 °C) are detrimental to educational attainment (Wargocki and Wyon, 2007), and school children feel lethargic when temperature and relative humidity are high (Salthammer et al., 2016). Urbanisation and climate change adversely affect thermal comfort and air quality in schools, and the impact of such exposure may go beyond discomfort or ill health, leading to a lifelong burden of disease (Salthammer et al., 2016).

Relationships between heat-related mortality and socio-economic and demographic factors vary regionally across the globe. Relationships have been found in some regions between heat-related mortality and factors such as age, gender, those classed as urban-poor, and areas with a lack of high-income earners (with income believed to be a good proxy for access to air conditioning), however, these are often not consistent between countries, in some cases showing no clear relationship for other socio-economic indicators (Hondula and Barnett, 2014; Johnson and Wilson, 2009; Yu et al., 2010). In the UK, regional long time-series analysis showed the strongest heat-mortality effects were in London, and the strongest cold effects in the East of England. A stronger heat effect was found for those living in urban areas, with no difference for cold effects. Indices of deprivation were not found to be a modifier for heat effects, and only slightly for cold effects in some rural areas, though this is influenced by how well individual circumstances are represented by area-level indicators (Hajat et al., 2007).

The World Health Organization (WHO) identified common heat risk factors including being elderly, having pre-existing cardiovascular or respiratory disease, living alone, working outdoors or being involved in heavy labour indoors close to industrial heat sources (World Health Organization, 2015). In some places, gender, nature of dwelling (e.g. hospital or care home), being urban and poor, and having certain medical conditions such as diabetes may also be linked with greater temperature-health effects, though causality is complex to determine as certain types of factors may interact with other determinants of health, as well as access to health-care systems (World Health Organization, 2015). Some indicators of socioeconomic status may be associated with heat-related health effects, though inconsistencies exist between studies, with different associations reported between countries, regions and cities within. There is also some evidence that temperature modifies the health effects of some air pollutants, such as ozone (Jerrett et al., 2009; World Health Organization, 2015).

1.6. Summary and aims

We have identified a wide range of factors that are likely to influence the risk of heat-related health effects, including housing type, population age, deprivation indices, and those residing in care and health facilities. People who experience multiple risk factors may be more vulnerable during periods of hot weather. An analysis of the spatial distribution of multiple risk factors across a region may reveal co-location of such factors, and identify places when strategies to mitigate heat risk might be most effective.

We address these issues as part of an urban case study for two recent significant heatwave events. We investigate firstly variations in environmental risk factors across the city (temperature, UHI intensity, and thermal comfort indices), and secondly, distribution of other factors which may relate to vulnerability from environmental risks (age, housing type, and deprivation index). A spatial analysis allows us to determine whether these sets of risks are co-located within our study city of Birmingham and the West Midlands region of the UK. Thirdly, we investigate the position of specific locations where sensitive populations are likely to be based, such as hospitals, care-homes, schools, and prisons, with respect to the intensity and position of the UHI, with the hypothesis that since these types of institutions are often situated in urban centres, populations may be at risk from exposure to high temperatures as a consequence of the effects of the UHI.

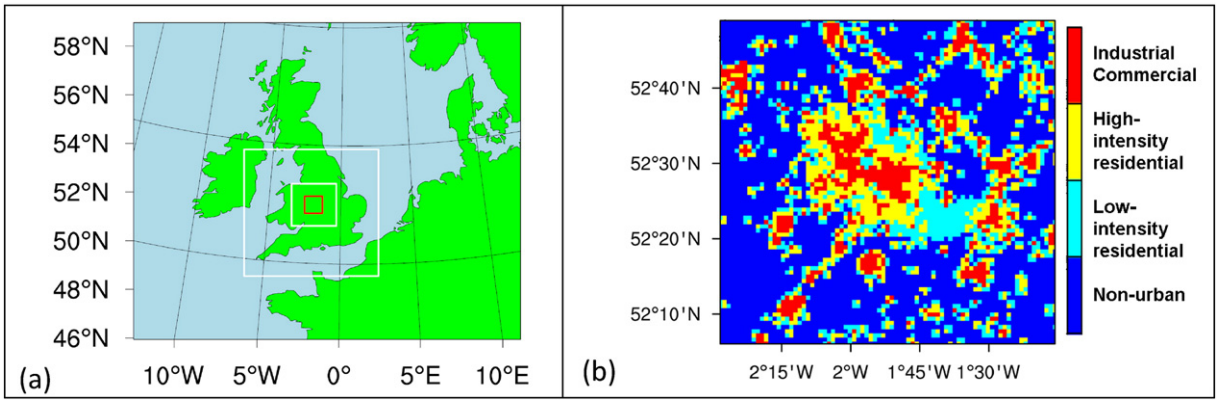

Fig. 1. (a) The domains covered by the WRF model simulation. The central domain (red box) is expanded in Fig. 1(b); (b) Urban classifications used in the urban canopy scheme in the WRF model in the central domain. The area shown covers approximately 80 × 80 km.

2. Methods and data

In this study we first modelled the ambient air temperature at a height of 2 m across the West Midlands, and quantified the UHI intensity across the region for the heatwave periods (August 2003 and July 2006) using a mesoscale meteorological model. Using GIS techniques we then extracted (from the modelled data) and analysed the ambient temperatures that correspond to different risk factors such as population age, dwelling type, and deprivation indices.

2.1. Modelling temperature

The Weather Research and Forecasting (WRF) model is a regional weather model that can be run at high resolution (1 km) to simulate the meteorology across a region (Chen et al., 2011). We used the WRF model with four nested domains (Fig. 1a) each with grid resolutions of 36 km, 12 km, 3 km, and 1 km in the smallest (central) domain, with feedback of variables from smaller grids to parent grids. The model time-step was 180, 60, 20 and 5 s for the four domains, respectively, with output every hour. Initial and lateral boundary meteorological conditions were provided by the European Centre for Medium-range Weather Forecasts (ECMWF) ERA-interim reanalysis (Dee et al., 2011) at a spatial resolution of 0.5° every 6 h. There were 39 pressure levels above the surface to 1 hPa. We used an urban canopy scheme, Building Energy Parameterisation (BEP), which models the effect of buildings on energy and momentum fluxes inside and immediately above the urban street canyons (Heaviside et al., 2015; Martilli et al., 2002). Information on building and road properties (e.g. building height, street canyon width, material properties such as albedo, thermal conductivity and heat capacity) is included for three urban categories: Industrial/commercial, high-intensity residential, and low-intensity residential across the West Midlands region (Fig. 1b). Details of parameters used for each urban category are given in Table 1a. Land-surface data used as an input to WRF for all domains were based on the US Geological Survey (USGS) 24-category land-use data, and for the inner domain we used two local datasets to generate the urban categories. We used the Noah Land Surface Model, a relatively complex community model, which is often coupled with an urban canopy scheme, and has four layers of soil moisture and temperature (Tewari et al., 2004).

The model has been previously run for this region for the August 2003 heatwave; details of the model simulation and validation are detailed in Heaviside et al. (2015). We have extended the analysis by re-running the 2003 heatwave using an updated version of WRF (v3.6.1), and including a further simulation run during a heatwave period in July 2006. In order to test performance, the model output is compared with observations from MIDAS observational weather stations across the West Midlands (Met Office, 2012). During heatwave periods, air temperature becomes more sensitive to surface moisture properties, which can be difficult for the model to capture. Soil moisture was adjusted in the model to better account for the unusually dry conditions, which led to improvements in the model performance (Fig. 2 and Table 2).

We ran the model for two heatwave periods (2nd–10th August 2003, and 16th–27th July 2006), and in order to quantify the UHI intensity, two simulations were run for each heatwave period. An 'urban' simulation was run as described above, using the urban categories shown in Fig. 1b, and is intended to represent the urban morphology of Birmingham and the West Midlands. The simulation is then run again, but with urban land cover replaced by rural cropland and pasture in the innermost domain, as a theoretical 'rural' case. By comparing results between the 'urban' and 'rural' simulations, the UHI intensity can be quantified.

The temperature that people experience or 'feel' can be influenced by a number of factors such as humidity, wind speed, exposure to direct solar radiation, and the amount of clothing they are wearing (Höppe, 1999; Steadman, 1984). National weather services sometimes provide a 'heat index' or 'apparent temperature' as part of weather forecasts during periods of warmer weather, to account for the effect of humidity, with assumptions about human body mass, height, clothing, amount of physical activity, sunlight and ultraviolet radiation exposure, and the wind speed. The heat index is calculated from temperature and relative humidity following the method of the NOAA Weather Prediction Center (www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml). This calculation is a refinement of a result obtained by multiple regression detailed in National Weather Service (NWS) Technical Attachment (SR 90–23). Accounting for the humidity only significantly influences the heat index above about 26 °C, and this calculation is not valid for extremes of temperature or humidity (Steadman, 1984).

2.2. Population and built environment characteristics

Population data are taken from the National Population Database (2015) gridded at 100 m resolution, which gives total population at each grid point. Information on age groups is available at Output Area[1] (OA) level from the most recent census (2011), and attached to each 100 m population point based on which OA the point falls within. The information is then summed across each WRF 1 km grid box.

Data on housing type was obtained at Lower Super Output Area[2] (LSOA) level from the most recent census (2011, available from infuse.

[1] Output Areas are the lowest geographical level at which census estimates are provided. There are 181,408 Output Areas in England and Wales. The average population per OA is 309.

[2] Lower Super Output Areas have an average of ~1500 residents and 650 households. Measures of proximity (to give a reasonably compact shape) and social homogeneity (to encourage areas of similar social background) are also included. There are 34,753 LSOAs in England and Wales. http://neighbourhood.statistics.gov.uk/.

Table 1
(a) Details of urban categories used in BEP. (b) General WRF model setup details.

(a)

Category		1: Industrial/commercial	2: High-intensity residential	3: Low-intensity residential
Albedo	Roof	0.1989	0.1997	0.2027
	Wall	0.1989	0.1997	0.2027
	Ground	0.1989	0.1997	0.2027
Surface emissivity	Roof	0.9239	0.9274	0.9292
	Wall	0.9239	0.9274	0.9292
	Ground	0.9239	0.9274	0.9292
Average building height		25 m	15 m	10 m

(b)

Model setting	Option	Reference
Long wave radiation	Rapid Radiative Transfer Model (RRTM)	Mlawer et al. (1997)
Short-wave radiation	Dudhia scheme	Dudhia (1989)
Boundary layer physics	Bougeault–Lacarrere (designed for use with BPE urban scheme)	Bougeault and Lacarrere (1989)
Urban physics	BEP urban scheme	Martilli et al. (2002)

ukdataservice.ac.uk). Data is available on the number of dwellings of each type within each LSOA. The number of dwellings of each housing type in each WRF model grid box is calculated by summing the fractions of each LSOA that intersect with each grid box, with housing assumed to be distributed evenly across each LSOA. This is combined with the 2 m air temperature simulated in the model during the heatwaves of 2003 and 2006, to estimate the average ambient temperature that different housing types across the West Midlands are co-located with. Information on housing type was available (e.g. detached, terrace, flat, etc.) but information on housing age was not recorded spatially.

The locations of hospitals, care homes, child care centres, schools, and prisons were considered where 'sensitive populations' are more likely to reside. The National Population Database provides information on these locations as they may have high densities of residents, many of whom may not be able to protect themselves (others have a duty of care towards them). People at these locations may be more vulnerable to harm and potentially harder to evacuate in an emergency situation. The temperature at the location of each of the centres of interest is extracted from the (hourly) model output using bilinear interpolation to the nearest modelled grid points. The mean temperature anomaly for each location is calculated by taking the mean temperature at the selected location over the heatwave period, and subtracting the mean temperature across the entire domain for the same period.

The English Indices of Multiple Deprivation (IMD) scores and ranks are produced periodically by the Department for Communities and Local Government, and are the official measure of relative deprivation for small areas (LSOA based on the 2011 census) in England. The IMD brings together 37 different indicators which cover specific aspects or dimensions of deprivation, such as income, employment, health and disability, education, skills and training, barriers to housing and services, living environment, and crime, which are then weighted and combined to create the overall IMD scores for each LSOA (ONS, 2007). For this work, IMDs for 2007 were used, as this is the closest available year to those modelled using WRF. The IMD score at LSOA level is attached to each 100 m population grid point, and then these are used to calculate population-weighted IMD scores for each WRF 1 km grid-box. Once the IMD scores for each WRF grid box are calculated, these are then associated with the temperatures from the WRF model, and ranked relative to each other, from least- to most-deprived. The data is then split into population deciles (in order of least to most deprived), and the associated temperatures plotted.

3. Results

3.1. Environmental risks

3.1.1. Temperature/heat index

Fig. 3a shows the modelled mean 2 m air temperature from 2nd–10th August 2003, and Fig. 3b shows the same for 16th–27th July 2006. The observed average and the overall minimum temperatures are higher by 1.3 °C in 2006 compared with 2003. Average daily maximum ambient temperatures are similar (difference of 0.3 °C), though temperatures reached at least 30 °C on more days in 2006 than 2003 (see Fig. S1 in Supplementary material). Comparison of Fig. 3 with the land use in Fig. 1b shows that urban areas are generally warmer than the surrounding rural areas in the West Midlands modelled domain.

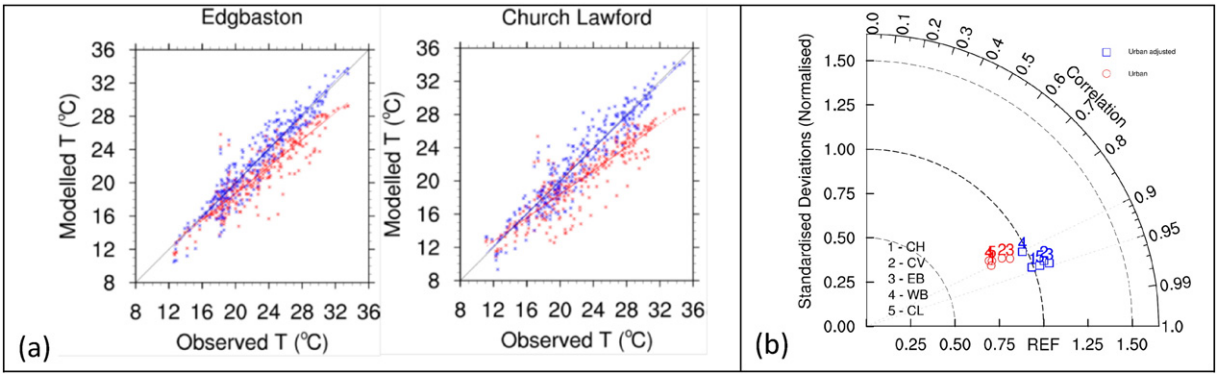

Fig. 2. (a) Modelled and observed ambient temperatures at MIDAS sites across the West Midlands in July 2006. (b) Taylor diagram showing statistical comparison between adjusted and unadjusted model. Unadjusted simulation is shown in red, and simulation with reduced initial moisture is shown in blue. A better comparison with observations is indicated by proximity to 'REF' on the horizontal axis.

Table 2
Statistical comparison between observed air temperature, and modelled temperatures (with soil moisture adjustment).

	Edgbaston		Coventry		Coleshill		Church Lawford	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
Mean (°C)	22.54	22.59	22.31	22.64	22.12	22.44	22.32	22.24
Standard deviation (°C)	4.54	4.95	4.78	5.11	5.19	5.15	5.21	5.40
RMSD (°C)	–	1.62	–	1.81	–	1.79	–	1.79
Correlation	–	0.94	–	0.94	–	0.94	–	0.94

The average calculated heat index for each of the heatwave periods is shown in Supplementary Fig. S2. The pattern and magnitude are very similar to the 2 m temperatures shown in Fig. 3. Additional discussion of the heat index may be found in the Supplementary material.

3.1.2. Urban Heat Island

The average UHI intensity across the whole period (defined as the difference in 2 m temperature between a simulation with urban land cover and a simulation with rural land cover) for both heatwave periods is shown in Fig. 4. Statistics for the two heatwaves are shown in Table 3.

While higher average temperatures were reached across the domain during the 2006 heatwave than the 2003 heatwave (Fig. 3), the magnitude and spatial distribution of the UHI intensity remains remarkably similar (Fig. 4). There are broad similarities in the spatial and temporal diurnal patterns of the UHI intensity between the two heatwaves (Fig. 4, Fig. S2), although some localised differences exist. The average UHI intensity in the city centre was slightly higher in 2003 (+2.2 °C in 2003 compared with +2.0 °C in 2006), but the UHI intensity at night time was larger in 2006 (+3.1 °C in 2006 compared with +2.5 °C in 2003).

By combining the data from the two heatwave periods, we have a larger dataset available to analyse the distribution of temperatures, and the UHI effects typical during heatwaves across the region. Fig. 5 shows the spatial distribution of the UHI intensity across the West Midlands, determined from both the August 2003 and July 2006 heatwaves combined, and illustrates the more intense UHI effect at night time compared with during the day.

The heat index and the difference in heat index between urban and rural simulations are shown in Supplementary material (Figs. S2 and S3), and very similar patterns to the UHI are shown. The specific humidity (i.e. water vapour mixing ratio) is lower in the urban simulation (Supplementary Fig. S4) due to the presence of urban surfaces replacing vegetated ones that would otherwise provide a supply of moisture to the surrounding air. Overall the average impact of urban surfaces on 2 m temperature and the average impact on the heat index are almost identical (Fig. 5 and Fig. S3).

3.2. Social factors

3.2.1. Housing

Buildings are an important modifier to population exposure to heat, with different types of housing being more or less susceptible to overheating, for example top-floor flats are more likely to overheat than detached houses (Beizaee et al., 2013; Symonds et al., 2017; Taylor et al., 2015). Fig. 6 shows the average 2 m air temperature that different housing types across the West Midlands are co-located with during heatwave periods, compared to the average temperature across the whole region. The anomaly represents the difference from the average temperature across the entire region for the time period considered (this temperature, representing zero anomaly, is labelled at the base of the vertical axis on the right). The average temperature across all housing types in the region is shown by the horizontal bar (again with absolute value labelled at the right axis). Detached houses, which tend to be located towards more suburban areas, are co-located with ambient temperatures almost 0.2 °C lower than the average for all housing types. By contrast, terraced houses and flats are co-located with ambient temperatures over 0.1 °C higher than the average for all housing types in the region, and 0.6 °C warmer than the whole domain average temperature. Our analysis shows that housing types which are more likely to overheat (e.g. flats) are often located in the warmest parts of the city, and the effects are much larger at night (Fig. 6b). The differences between ambient temperatures for each housing category are all statistically significant ($p < 0.05$; see Supplementary material for details). While the temperature variation between different housing types is <1 °C, it should be noted that the average UHI intensity for the region was about 0.6 to 0.7 °C (and just over 2 °C in the centre of the urban area) during heatwaves.

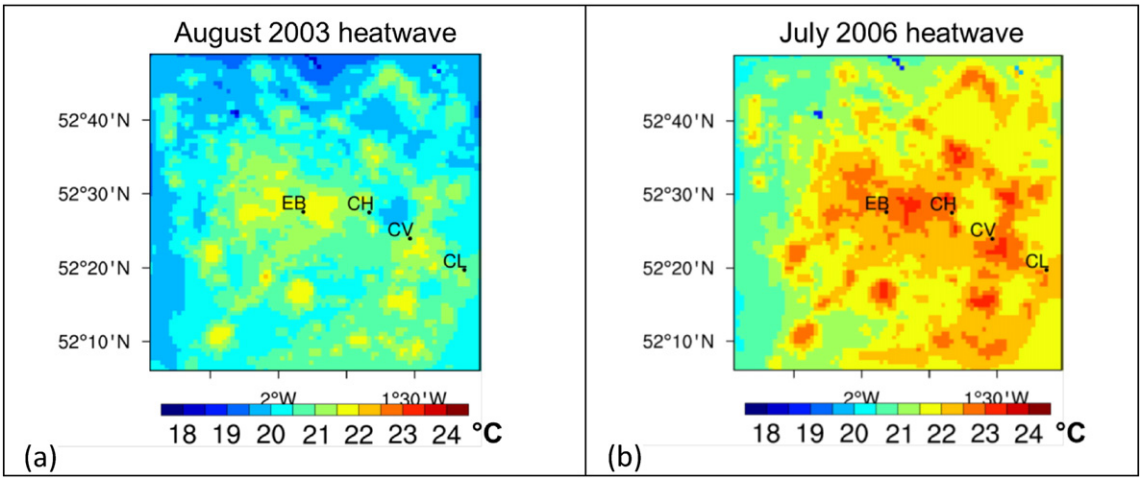

Fig. 3. Mean 2 m air temperatures simulated across the West Midlands during (a) heatwave period from 2nd–10th August 2003, and (b) for the heatwave period during 16th–27th July 2006. Lettered points show monitoring stations used for model validation. EB = Edgbaston; CH = Coleshill; CV = Coventry; CL = Church Lawford.

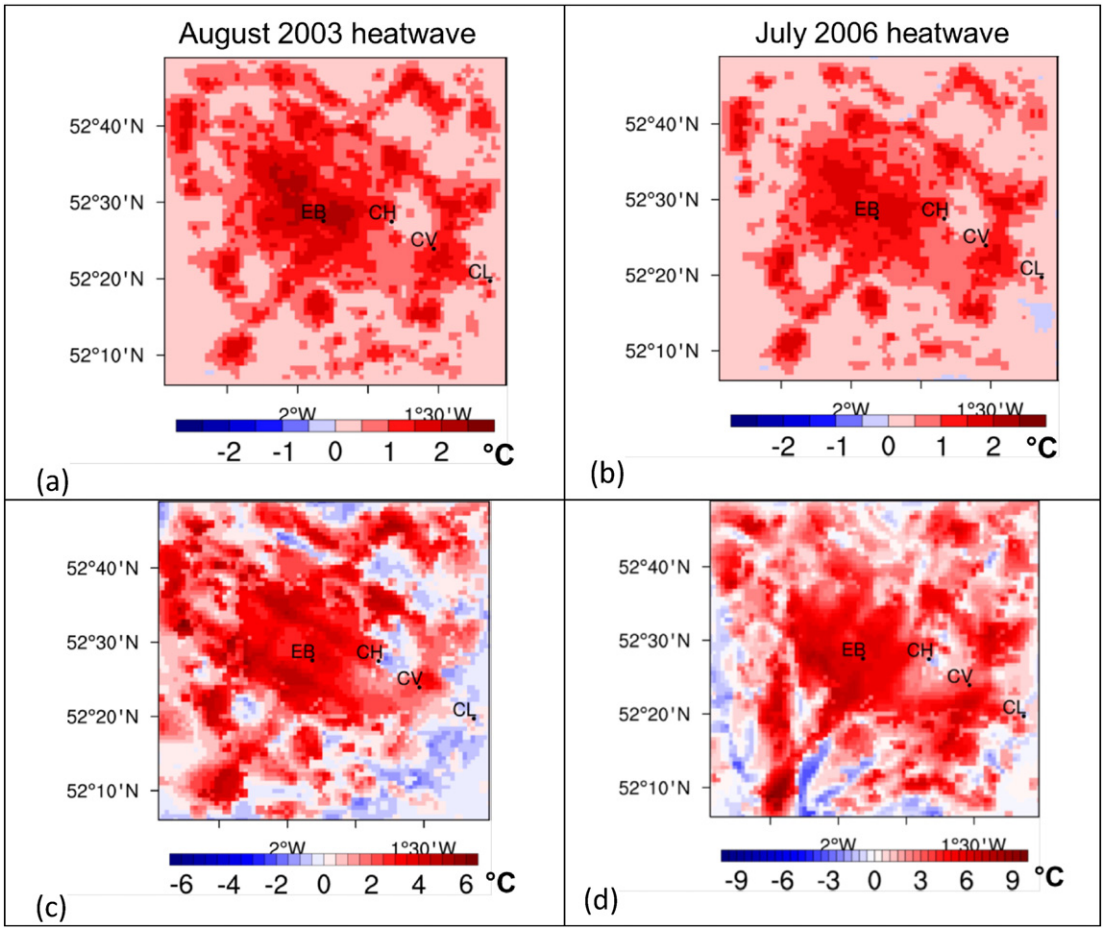

Fig. 4. Mean UHI intensity for the whole time-period across the West Midlands (a) 2nd–10th August 2003, and (b) 16th–27th July 2006. Snapshots of high UHI intensity for each period are shown in (c) 11 pm 5th August 2003, and (d) 11 pm 17th July 2006. Lettered points show monitoring stations used for model validation. EB = Edgbaston; CH = Coleshill; CV = Coventry; CL = Church Lawford. Note that the colour scales are not all equal.

3.2.2. Population age

Fig. 7 shows the average outdoor temperature anomalies different age groups are exposed to, based on residential address. The anomaly represents the difference from the average temperature across the entire region for the time period considered (this temperature, representing zero anomaly, is labelled at the base of the vertical axis on the right). The average across all age groups is shown by the horizontal bar (again with absolute value labelled at the right axis). The whole West Midlands population is exposed to temperatures about +0.6 °C higher than the regional average (as populations reside in more urbanised areas) (Fig. 9a). Young adults and the very young are exposed to slightly higher temperatures than the population average (e.g. 20–24 year olds reside in areas +0.7 °C warmer than the regional average of +0.6 °C), while the elderly are exposed to slightly lower temperatures than the population average (e.g. 65–75 year olds reside in areas +0.5 °C). During the daytime, there is only a modest difference in ambient temperatures exposure in comparison to the regional average; however at night time, population-weighted temperatures are over 1 °C higher than the regional average (Fig. 7b,c). It should be noted that these figures are based on residential population, so those present in health and care centres are not considered here. Overall, the differences in exposure to ambient temperatures for different population groups are modest, likely a reflection that population age groups are less heterogeneously distributed across this region. The differences between ambient temperatures for each age group are all statistically significant ($p < 0.05$; see Supplementary material for details), with the exception of the 15 and the 16–17 year old age groups ($p = 0.25$), the 60–64 and 65–69 year old age groups ($p = 0.069$), and the 85–89 and 90+ year old age groups ($p = 0.055$).

Table 3
Statistics for modelled temperature and the UHI intensity for the two heatwave periods in August 2003 and July 2006.

		Average temp (°C)	Average UHI (°C)	Daytime[a] average UHI (°C)	Nighttime[a] average UHI (°C)	Max UHI (°C)
Aug 2003	Regional[b]	20.5	+0.7	+0.5	+1.0	+6.1 (5 pm 10th; 11 pm 5th; 9 pm 9th)
	City centre[c]	21.7	+2.2	+2.0	+2.7	
July 2006	Regional[b]	21.7	+0.6	+0.1	+1.2	+9.6 (11 pm 17th)
	City centre[c]	23.0	+2.0	+1.0	+3.1	

[a] Daytime is defined as 08:00–19:59; Nighttime is 20:00–07:59.
[b] Regional is the whole area shown in Fig. 1a.
[c] City centre is a point in the centre of Birmingham city.

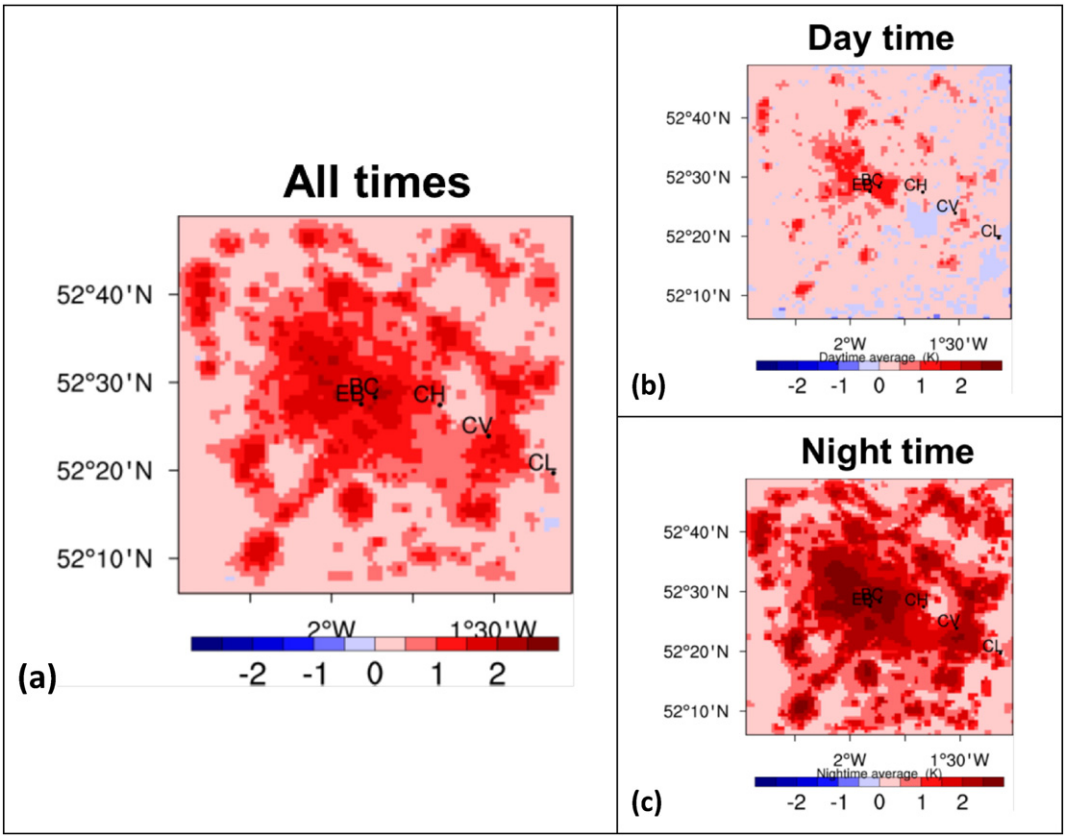

Fig. 5. (a) Average UHI intensity during heatwave periods (2–10 Aug 2003 and 16–27 July 2006) across the West Midlands; Averages over (b) daytime and (c) night time. Average UHI intensity was +2.1 °C (+1.4 °C in daytime, +2.9 °C at night time).

3.2.3. Deprivation

Fig. 8 shows the average ambient temperature exposure for increasingly deprived population deciles, calculated from population weighted scores across the domain ranked relative to each other. The anomaly represents the difference from the average temperature across the entire region for the time period considered (i.e. day, night, or all times). The horizontal line shows the population weighted temperature for the time period. The most deprived decile of population across the

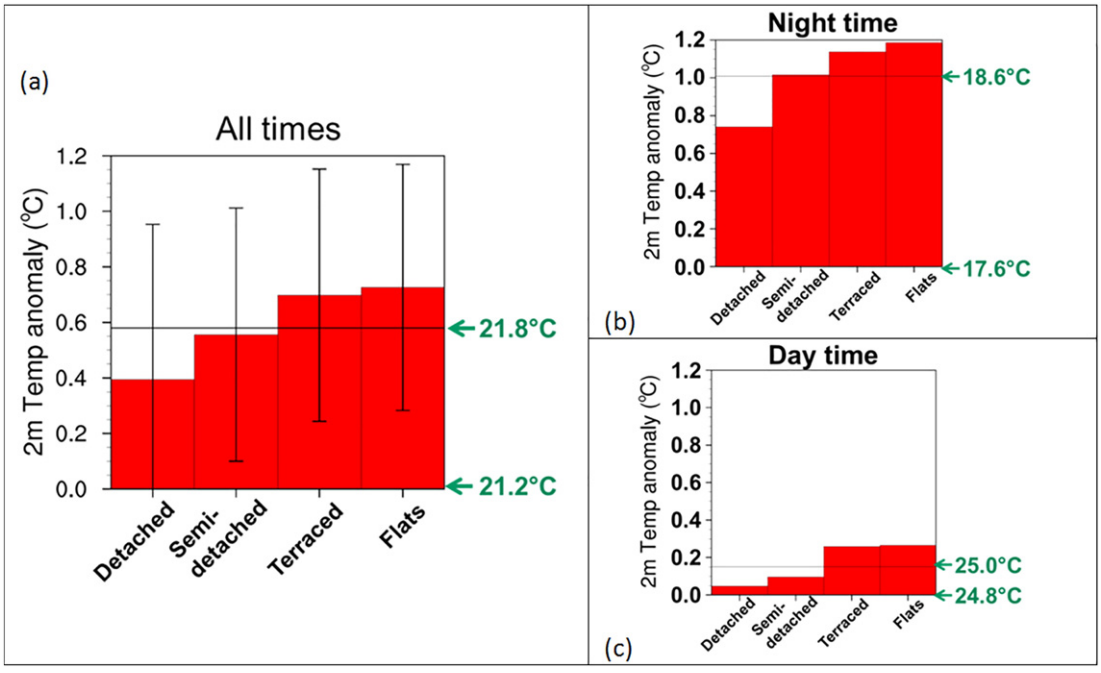

Fig. 6. (a) Average outdoor temperature anomaly (compared with the average across the domain during the heatwave period) with standard deviations plotted over the bars. The analysis is also broken down into (b) night time and (c) day time.

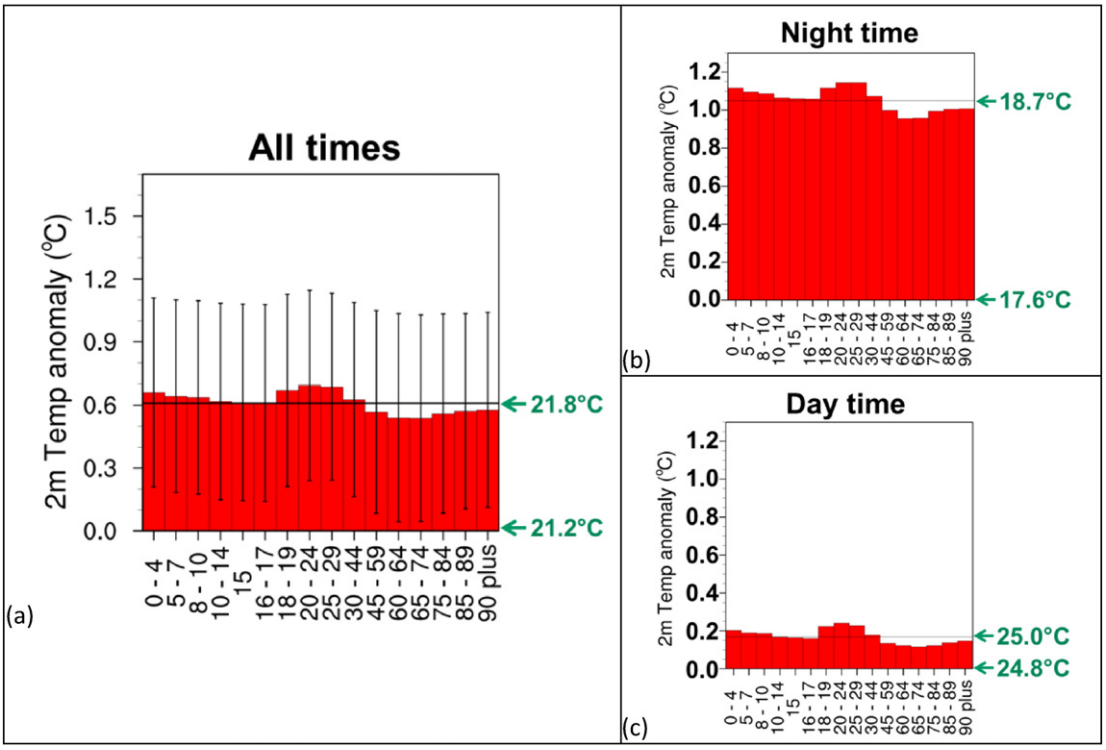

Fig. 7. (a) Average outdoor temperature anomaly (compared with the average across the domain during the heatwave period) for different age groups across the West Midlands, with standard deviations plotted. The analysis is also broken down into (b) night time and (c) day time.

region is exposed to temperatures +1.0 °C higher than the average for the region (+0.5 °C during the day, and +1.5 °C at night). The most deprived decile of population for the region experiences temperatures consistently higher than the average for the region, even during the daytime (each decile represents ~0.5 million people). The overall deprivation scores for all LSOAs in England range from 0.37 to 85.46. For comparison, the deprivation scores calculated for each decile in Fig. 8 range from 6.08 to 56.17, placing them around the 12% and 96% most deprived relative to England. The differences between ambient temperatures for each deprivation decile are all statistically significant

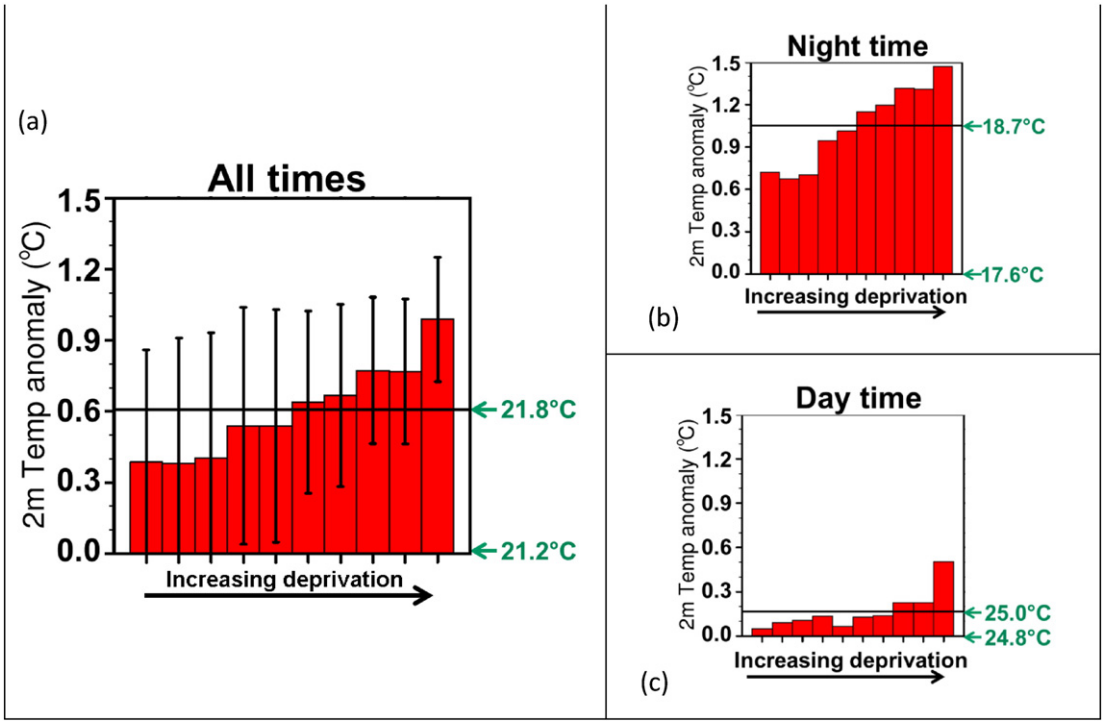

Fig. 8. (a) Average outdoor temperature anomaly (compared with the average across the domain during the heatwave period) for population deciles ranked by deprivation across the West Midlands, with standard deviations plotted. The analysis is also broken down into (b) night time and (c) day time.

($p < 0.05$; see Supplementary material for details), with the exception of deciles 4 and 5 ($p = 0.989$).

3.3. Location based assessment of vulnerability from heat

Sensitive receptors such as hospitals, care homes, child care facilities, schools, and prisons tend to be located in the most highly urbanised areas of the region, with the exception of prisons which are often located on the outskirts of the city. The distribution of temperature anomalies for each location type is shown in Fig. 9. The anomalies are based on the number of receptors (i.e. buildings), and not the population at each location, as this will fluctuate. The majority of hospitals, care homes, schools and child care centres are located in areas warmer than the domain average (94% of hospitals, 90% of care homes, 87% of schools, and 88% of child care centres). There are seven prisons located within the study area, with only two of these being warmer on average (Fig. 9e).

4. Discussion

In this study we used hourly ambient temperature data at high spatial resolution (1 km) across a densely populated region of the UK, capturing temperature variation across the period of two different heatwave episodes. We employ environmental modelling techniques to examine human health in relation to heat exposure during heatwaves, which will become increasingly important in the future as climate change is projected to increase heat-health impacts. Previous studies have examined the spatial distribution of vulnerability to heat risk across a region, often using ambient temperatures that are time-varying but have no spatial variation, or that are well represented spatially but only for a single or limited time frame (Taylor et al., 2015; Tomlinson et al., 2011; Wolf and McGregor, 2013). By using well-validated meteorological modelling techniques, we have generated an ambient temperature dataset, based on modelled output, at high temporal and spatial resolution from which to calculate ambient temperatures exposure co-located with various risk factors that relate to and influence heat-related health effects. These include population-weighted temperature exposure and the relationship between UHI intensity and demographic factors such as age group. Previous studies have mapped such risks, but our work extends this analysis by calculating the ambient temperature weighted according to distributions of different housing types, population (including age), and deprivation score, all being factors that influence heat-health effects. We have also broken down the analysis by day and night; while the whole region is warmest during the daytime (and urban areas are still warmer than rural ones at this time), the spatial variation in temperature across the region is much greater at night, due to the influence of the UHI (Fig. 5). While there is no clear indicator of which temperature metric is most strongly correlated with mortality, and there is variation between countries and cities (Davis et al., 2016), high mortality ratios have been associated with high night time land surface temperatures during the August 2003 heatwave in Paris (Dousset et al., 2011), and there is evidence that higher night time temperatures have a detrimental impact on sleep quality, which is linked with other negative health outcomes (Lack et al., 2008).

We found that almost all locations where sensitive populations are likely to be located (hospitals, care homes, schools, colleges) were warmer than the regional average by up to 2 °C, and the number that are warmer is greater at night time (Fig. 9). Of the seven prison locations within the study area, most were located in more rural or suburban areas, and therefore were not exposed to higher average ambient temperatures for this region.

Locations classified as hospitals here include a few small treatment centres such as family planning, dialysis centres, etc., and therefore do not necessarily have resident populations who might be exposed to the larger temperature anomalies at night. Locations classed as care homes have a high density of residents, present day and night, and also include centres with specialised facilities for those with mental health issues, sensory impairment, learning difficulties, and those who misuse drugs and alcohol. Child care centres have a duty of care to protect people who cannot protect themselves, with potentially high populations, including nurseries, crèches, toddler groups, afterschool clubs, holiday schemes, and youth clubs. School locations are unlikely to be occupied at night, when temperature anomalies are higher, and those of school age are exposed to ambient temperatures close to the average for the population (though still above regional average). While colleges have very high populations, they again are unlikely to be occupied at night.

The anomalies presented here are based on ambient temperature, although buildings play an important role in determining actual exposure, particularly at night time. Studies using building simulations to estimate indoor temperatures find a significant influence of building characteristics on indoor temperatures (Taylor et al., 2015). However these studies often use a single ambient temperature across all dwelling types, whereas this study shows that different building types are likely to be exposed to different ambient temperatures across a region. Our study could help inform development of inputs to building models by providing a modifier to ambient temperature based on the likely outdoor temperatures for a particular building type.

While we have included the highest spatially resolved data that was available at the time, the analysis makes some assumptions about distribution of certain factors. Data for housing types at LSOA level, and population ages at OA level was the finest level of data that was available. Any variations that may exist within an individual LSOA or OA respectively could not be captured by this analysis. The BEP multi-layer urban canopy scheme used with WRF can capture the effects of the built environment on energy and momentum fluxes (accounting for shading and reflections by buildings) at sub-grid scale, providing a suitable representation of how urban areas influence meteorology in a weather model such as WRF. However, microclimatic effects at individual building level are not explicitly captured, as regional weather models can only be run down to 1 km horizontal grid scale constrained by the valid sub-grid scale turbulence schemes, and therefore results for individual locations interpolated from the 1 km grid may have additional variation. The IMDs are a measure of relative deprivation, calculated by weighting data on different indicators that can be used as measures of deprivation. The IMDs are calculated periodically, and although it is a good measure for comparing areas with each other, this measure cannot be easily compared with other years or used to identify trends, as the ranking is performed separately each time a new dataset is released.

This study focuses primarily on the effects of heat, although other environmental or socioeconomic factors in cities that may impact health could be considered in future studies. Such factors may include air pollution, flood risk, social isolation or greenspace. Cold effects could also be investigated. These and other factors identified as influencing health may be included in future studies to develop and overall environmental risk map for cities. Finally, this study examines past heatwave events in two years across the UK, allowing model validation against observations. Future scenarios under climate change could be considered in further work.

5. Conclusions

Previous research suggests that the UHI may contribute around half of the heat related mortality experienced during heatwaves (Heaviside et al., 2016). Increasing urbanisation and climate change will increase heat related health risks in urban areas. We have developed a novel risk mapping methodology that combines high spatial resolution modelling of temperature, population age, and building types to identify locations and population sub-groups at higher health risk during heatwaves. We have simulated and quantified the magnitude and characteristics of the UHI in the West Midlands during two heatwave periods (August 2003 and July 2006), using the WRF-BEP model. The

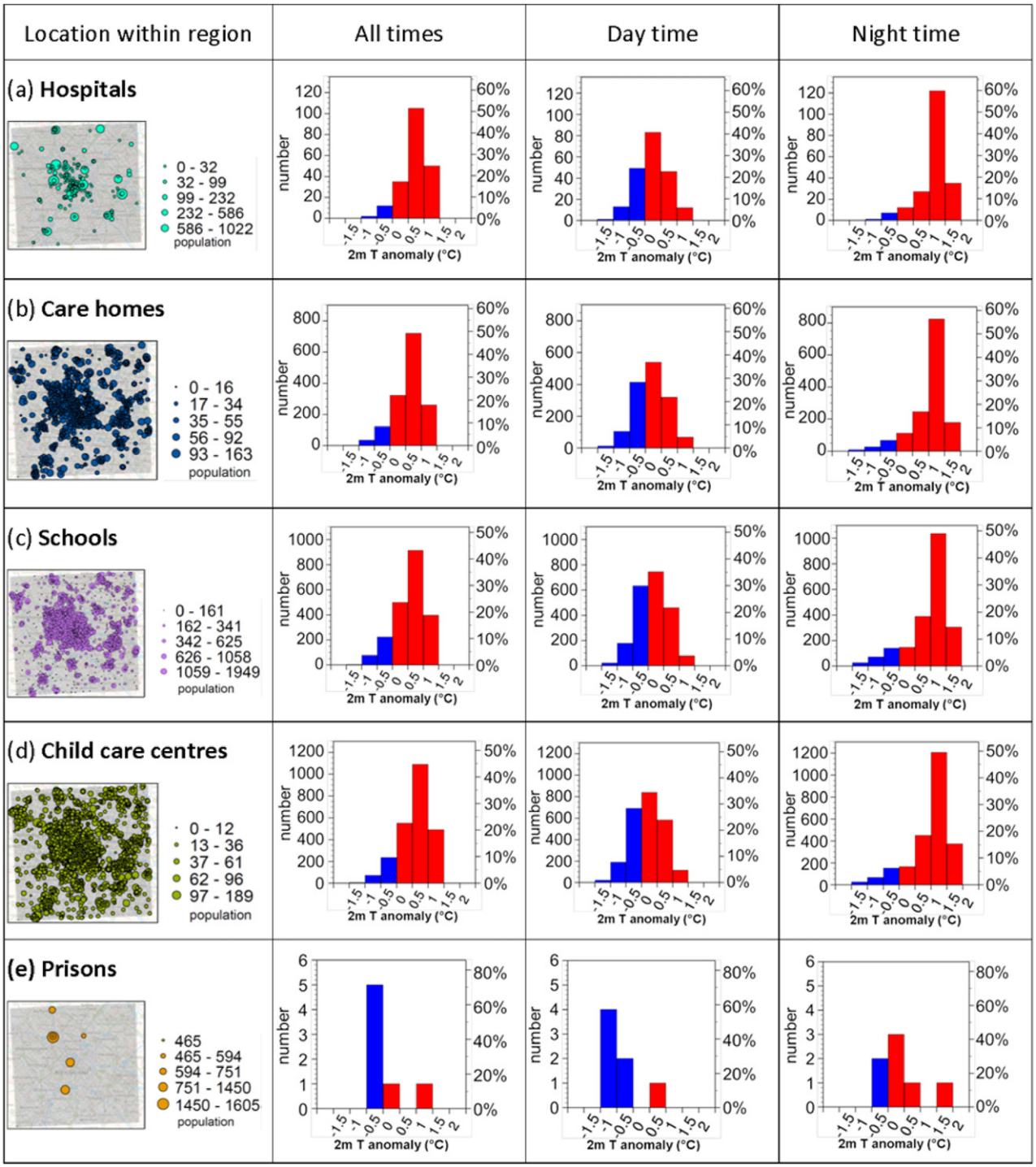

Fig. 9. Distribution of average ambient 2 m temperature at (a) hospitals, (b) care homes, (c) schools, (d) child care centres, and (e) prisons across the West Midlands. The first column shows the distribution of these locations across the West Midlands, and the next three columns represent the average anomaly averaged first across all times of day, and then broken down into average daytime anomaly (8 am–8 pm), and average night time anomaly (8 pm–8 am). The average temperature across the domain (used as the reference temperature) is 21.8 °C. Red = positive anomaly (warmer); Blue = negative (colder).

UHI intensity across the region is on average 2.1 °C, reaching up to 9.4 °C, and there is strong spatial heterogeneity in ambient temperature across the region, particularly at night. Spatial analysis using GIS techniques shows that locations where people already more vulnerable to the effects of exposure to heat (e.g. the elderly, those with pre-existing health conditions, and those dependent on others for care) may reside, tend to be located in the hotter parts of the region. Sensitive receptors (94% of hospitals, 90% of care homes, 87% of schools, and 88% of child care centres) are co-located with higher than the average air temperatures across the West Midlands. Buildings that are more susceptible to overheating, such as flats, are exposed to higher ambient temperatures than other housing types.

Interventions such as urban greening or building modifications such as cool roofs may help offset some of the UHI intensity, and reduce the spatial disparity in ambient temperatures, particularly at night. The results from this work could help identify which factors are most strongly

correlated with ambient temperature, and help target resources and interventions, as well as focus health messaging during heatwaves to the greatest effect.

Further research is needed to estimate the spatial heterogeneity of factors influencing heat risk in cities. In addition, future work should consider the health impacts and potential benefits that UHI mitigation techniques in a UK city would have on building overheating, as well as the co-benefits or other unintended environmental consequences that may occur in a city.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2017.08.062.

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